Opioid Use Disorder: Decision Support for Healthcare Professionals

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Abstract

Opioid Use Disorder (OUD) is defined as deviating from the physician's prescription of a specific opioid. The OUD patients will require expensive inpatient treatment followed by a long-term outpatient treatment. We present a decision support system for opioid prescriptions, inpatient treatment (detoxification), and outpatient treatment by healthcare professionals. We analyzed the impact of inaccuracy in PDMP, decision scenarios, and effectiveness of decisions in outpatient scenarios on the opioid resource requirements. The proposed DSS will lead to better decision making using both the risk score and patient's condition.

Keywords

Decision support systems, opioid use disorder (OUD), Markov model, evaluation.

Introduction

The use of prescription opioids has increased exponentially in the last decade. Opioid Use Disorder (OUD) is defined as deviating from the physician's prescription of a specific opioid (Finley et al. 2017; Sinha et al. 2017). According to NIH, the total cost of opioid abuse in the US is approaching $100B per year with more than 2 million people misusing opioids (NIH 2019). OUD has become a major societal challenge for patients, family members, healthcare professionals, regulators, and society. The susceptibility to OUD is related to the type of opioid prescribed and medical condition (co-morbidities) of the patient including current and past conditions. This could lead to three different forms of OUD (mild, moderate, or severe) (APA 2013), all of which are considered and treated as chronic diseases. The OUD patients at any of the three levels, with or without overdose events, will require expensive inpatient treatment (Chintha et al. 2018; Ivanov and Tacheva 2018) followed by a long-term outpatient treatment.

In this paper, we focus on the factors behind the increased availability of prescriptions for opioids. Even with awareness, healthcare professionals underestimate the risks of opioid abuse (Brown et al. 2011). This along with the level of workload can result in prescription decisions that are sub-optimal. A Center for Disease Control study shows an urgent need for improved prescribing practices (CDC 2015). The study found that prescribing practices varied widely among states and a small minority of prescribers were responsible for most prescriptions. The findings provide extensive support for improving opioid prescribing practices (CDC 2015).

Many healthcare professionals rely on individual state's Prescription Drug Monitoring Program (PDMP), which are statewide databases containing prescriber and patient-level prescription data on select drugs of abuse. These databases are used by medical professionals or law enforcement officials to identify patients with prescription drug use patterns indicative of abuse or providers engaging in illegal activities (Reifler et al. 2012). There are numerous challenges with relying only on PDMPs alone. These include (a) lack of awareness related to detailed functionalities of PDMPs, (b) lack of interoperability among different states, (c) varying goals, objectives, and functionalities of different programs, (d) lack of effectiveness due to the reliance on intra-state prescriptions and not able to track all prescriptions and polypharmacy across states, and (e) not comprehensive and reliable enough to be the only source of information for decision making. The epidemic can be addressed by several different interventions such as monitoring (Varshney 2015). In

this paper, we focus on a proactive intervention, which involves providing comprehensive information related to potential misuse and abuse of medications to healthcare professionals. More specifically, we present a decision support system to improve decisions related to opioid prescriptions, inpatient treatment (detoxification), and outpatient treatment by healthcare professionals.

The contributions of this paper are (a) literature review of how decision support for a prescription is studied in the literature, (b) decision support system (DSS) for opioid prescriptions by healthcare professionals, and (c) model and results to study the impact of interventions. In the next section, we present the literature review for decision support, followed by some results. Finally, the discussion and conclusion are presented.

Literature Review

We performed a comprehensive literature search on "Opioid AND Prescription AND (Intervention OR management OR decision)" in Web of Science, PubMed, MEDLINE, IEEE Xplore, ACM, and AIS e-library databases (Figure 1). We identified a total of 127 articles. After removing 69 duplicate and/or redundant articles, 58 articles were assessed to explore the interventions by healthcare professionals for prescribing opioids. Further, 43 articles were not focusing on interventions for healthcare professionals. Finally, the remaining 15 articles were analyzed for decision making by the healthcare professionals for prescribing opioids. The classification of articles (Table 1) includes: therapeutic intervention (2 articles), educational intervention (2 articles), decision support system (4 articles), composite interventions (3 articles), and regulatory interventions (4 articles). These categories are not necessarily disjoint. For example, multiple strategies by healthcare professionals (HP) may be influenced by regulatory theme. Multiple strategies may also include DSS as one component. The education may involve learning of DSS components such as Prescription Drug Monitoring Programs (PDMPs). Regulatory intervention may also affect the design, implementation, and use of DSS such as PDMPs.

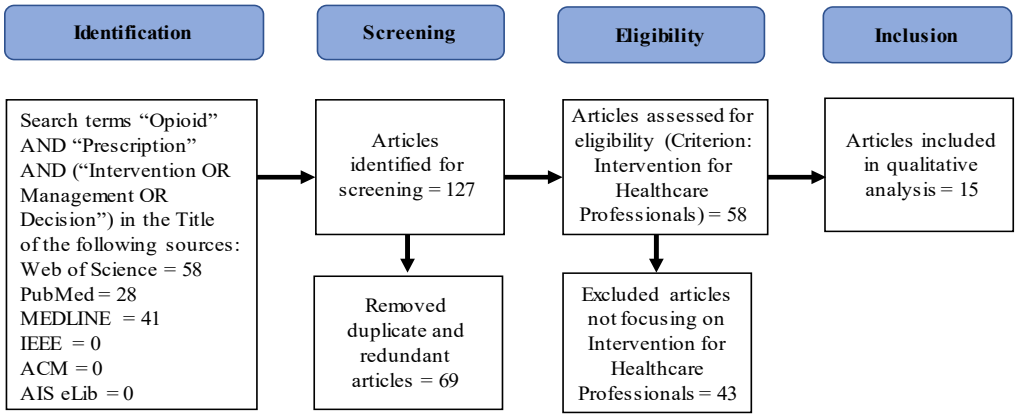

Figure 1. Literature Review of Interventions for Opioid Prescription

Type of Intervention	Frequency in our Sample
Therapeutic alliance (patient and HP/pharmacist)	2
Educational intervention for HP	2
DSS for HP	4
Composite interventions by HP	3
Regulatory	4
Total = 5 types of interventions	Total = 15

Table 1. State and Federal Monitoring on ORR

Decision Support System for Healthcare Professionals

The decision support system for healthcare professionals will be based on the concept of integrating PDMP data with EHR data (Shen and Li 2019). In this paper, we propose to integrate the information from multiple sources (Kyung and Lim 2019; Nassel et al. 2018) including smart medication box, self-reporting, and monitoring into the DSS. This information along with the clinical knowledge support from other healthcare professionals will help in developing a more robust prescription system. In addition to monitor the past prescription patterns for the patient this will add the risk score calculation functionality for healthcare professionals based on the current symptoms, history of substance abuse, and other health comorbidities of the patients.

Model and Results

Using the proposed DSS in the previous section and the three states of prescription, inpatient treatment, and outpatient treatment we developed a Markov chain model (Sonnenberg and Beck 1993) of decision making as shown in Figure A1 of Appendix. The detailed model is shown in Appendix A1 (Equations A1-A3, B1-B4, C1-C2). This model helps the healthcare professionals to analyze the opioid resource requirements (ORR). Table 2 shows that the inaccuracy or increasing error in PDMP will lead to less accurate prescriptions resulting in higher opioid resource requirements. Table 3 shows the ORR for different scenarios. Scenario 1 considers only the risk score, the scenario considers only the current condition of the patient, and scenario 3 considers both risk score and current condition. As shown in Table 3 when both risk scores and current conditions of the patient are considered the ORR is comparatively low. Table 4 shows the effectiveness of the decision made by doctors in outpatient treatment. We can see that as the effectiveness of decision making in outpatient treatment increases the opioid resource requirement decreases leading to better decision making with minimal resources.

Inaccuracy	Modified (actual) Risk Score	Prescription Probability	P_P	P_I	P_O	Opioid Resource Requirements (ORR)
0.0	0.50 (0.50)	.625	.243	.454	.303	0.678
0.25	0.438 (0.50)	.656	.234	.460	.306	0.683
0.5	0.375 (0.50)	.688	.225	.465	.310	0.688
0.75	0.313 (0.50)	.719	.218	.469	.312	0.690
1	0.25 (0.50)	.750	.211	.474	.315	0.695

Table 2. Impact of State and Federal Monitoring on ORR

Decision Scenario	Risk Score	Prescription Probability	P_P	P_I	P_O	Opioid Resource Requirements (ORR)
Scenario 1 (100% Risk)	0.0	1.0	1.0	0.0	0.0	0.3
	0.25	0.75	0.348	0.391	0.261	0.626
	0.5	0.5	0.286	0.429	0.286	0.658
	0.75	0.25	0.348	0.391	0.261	0.626
	1.0	0.0	1.0	0.0	0.0	0.3
Scenario 2 (100% current condition)	0.0	0.75	1.0	0.0	0.0	0.3
	0.25	0.75	0.348	0.391	0.261	0.626
	0.5	0.75	0.211	0.474	0.316	0.695
	0.75	0.75	0.151	0.509	0.340	0.724

	1.0	0.75	0.118	0.529	0.353	0.741
Scenario 3 (50% risk and 50% current condition)	0.0	0.875	1.0	0.0	0.0	0.3
	0.25	0.75	0.348	0.391	0.261	0.626
	0.5	0.625	0.243	0.454	0.303	0.678
	0.75	0.5	0.211	0.474	0.316	0.695
	1.0	0.375	0.211	0.474	0.316	0.695

Table 3. The Role of Prescription decisions on ORR

Effectiveness of Decisions in Outpatient Treatment	P_P	P_I	P_O	Opioid Resource Requirements (ORR)
0.0	0.0	0.667	0.333	0.834
0.25	0.127	0.556	0.317	0.753
0.5	0.243	0.454	0.303	0.678
0.75	0.348	0.362	0.290	0.611
1	0.444	0.278	0.278	0.550

Table 4. Impact of Decision Making in Outpatient Treatment on ORR

Discussion and Work in Progress

The proposed DSS for healthcare professionals can improve decision making for prescription opioids. We analyzed the impact of inaccuracy in PDMP, decision scenarios, and effectiveness of decision making in outpatient scenarios on the opioid resource requirements. We observed that ORR is decreasing with a decrease in error, balanced consideration of risk score and current condition, and an increase in the effectiveness of outpatient treatment. This leads to the conclusion that the proposed DSS for healthcare professionals will lead to better decision making for healthcare professionals.

Currently, we are working on getting results for the inpatient treatment state. We are working towards designing and evaluating nationwide drug monitoring systems by integrating state PDMP systems. Also, we have started evaluating the significance of decision support for HP at all three different states of OUD (prescription, inpatient treatment, and outpatient treatment). The goal of this comparison is to identify at which state decision making will be most effective. We are exploring the IT-support for decision making by healthcare professionals including doctors and pharmacists.

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Appendix:

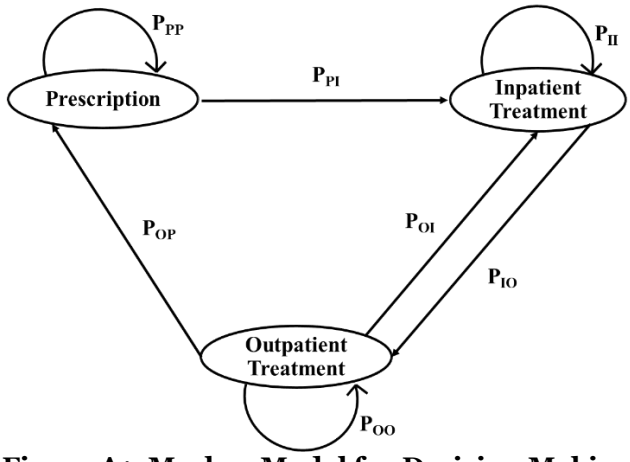

Figure A1. Markov Model for Decision Making

Solving the above chain, we obtain the following sets of equations. The steady-state probability of being in Prescription state (P_P) is given as

$$P_P = \frac{\frac{P_{OP}}{1-P_{PP}}}{1+\left(\frac{P_{OP}}{1-P_{PP}}\right)+\left(\frac{1-P_{OO}}{P_{IO}}\right)} \quad \textbf{(A1)}$$

The steady-state probability of being in inpatient treatment state (P_I) is given by

$$P_I = \frac{\frac{1-P_{OO}}{P_{IO}}}{1+\left(\frac{P_{OP}}{1-P_{PP}}\right)+\left(\frac{1-P_{OO}}{P_{IO}}\right)} \quad \textbf{(A2)}$$

Probability of being in outpatient treatment state (P_O) is given by

$$P_O = \frac{1}{1+\left(\frac{P_{OP}}{1-P_{PP}}\right)+\left(\frac{1-P_{OO}}{P_{IO}}\right)} \quad \textbf{(A3)}$$

For Prescription state, $P_{PP} = 1 - P_{PI}$ and $P_{PI} = \text{Risk}_{\text{Score}} \times \text{P}_{\text{PRESC}}$ **(B1)**

$$\text{P}_{\text{PRESC.Scenario1}} = 1 - \text{Risk}_{\text{Score}} \quad \textbf{(B2)}$$

$$\text{P}_{\text{PRESC.Scenario2}} = \text{Current}_{\text{Condition}} \quad \textbf{(B3)}$$

$$\text{P}_{\text{PRESC.Scenario3}} = \text{Weight1} \times (1 - \text{Risk}_{\text{Score}}) + \text{Weight2} \times \text{Current}_{\text{Condition}} \quad \textbf{(B4)}$$

Prescription probability for polypharmacy is $PP_{Poly} = \sum_{R=1}^{N} \binom{N}{R} (P_{Presc})^R (1 - P_{Presc})^{N-R}$ **(C1)**

The Opioid Resource Requirements (ORR) $ORR = \sum_{I=1}^{M} \text{P}_\text{I} \times R_I$ **(C2)**